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Survey-data Estimates of the R&D Depreciation Rate

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Abstract

This paper presents estimates of the R&D depreciation rate using survey data on Australian inventions. Its novelty is twofold. First, it relies on direct observation of the revenue streams of inventions. This is in sharp contrast with previous studies which all rely on models based on indirect observation and require strong identifying assumptions. Second, it presents estimates of the effect of patent protection on the depreciation rate. We find that the yearly depreciation rate varies between 1 and 5 per cent, although as much as 40 per cent of the decline in value occurs within the first two years. We further find that patent protection slows down the erosion of profits by about 1–2 percentage points.

Keywords: appropriability, creative destruction, depreciation of R&D, obsolescence, patent premium, returns to R&D

JEL Codes: O32, O33, O34

1. Introduction

Intangible assets are attracting major academic and policy interest in today's knowledge economies. Intangible assets are assets that are not physical in nature, such as knowledge generated through investment in research and development (R&D), yet deliver concrete economic benefits. Since the seminal work by Solow (1956), research has established that intangible assets account for a significant proportion of firms' value and are an important driver of productivity growth (Adams 1990; Coe and Helpman 1995; Lev and Sougiannis 1996; Crépon et al. 1998; Webster 2000). However, our understanding of intangible assets is still limited and many open questions remain.

One such question is the speed at which these assets depreciate. This paper focuses on the private rate of depreciation of R&D assets, defined as the rate of decay of appropriable revenues that these assets generate (Pakes and Schankerman 1984).¹ Griliches (1998) and Hall (2005) talk about the 'depreciation problem' of R&D assets, which arises from the difficulty in reconciling depreciation rates obtained using different methodologies. Understanding the drivers of R&D depreciation, and getting reliable estimates, will help answering several open economic questions. The R&D depreciation rate informs about the speed of technological change and is essential for estimating the returns to R&D investments (Pakes and Schankerman 1984; Esposti and Pierani, 2003; Hall et al. 2010). In fact, Hall (2005:342) argues that measurement of the depreciation of R&D assets is the 'central unsolved problem in the measurement of the returns to R&D'. In addition, because the R&D depreciation rate is endogenous to R&D investments, it is also central to the understanding of industry dynamics (Caballero and Jaffe 1993; Jovanovic and Nyarko 1998; Pacheco-de-Almeida 2010). Finally, it is also of practical relevance in other fields such as growth accounting studies, where it is used to build R&D capital stock and to compute the rental price of R&D capital (Nadiri and Prucha, 1996; Bernstein and Mamuneas 2006; Corrado and Hulten 2010).

Within this context, this paper presents novel estimates of the R&D depreciation rate using data from the Australian Inventor Survey (AIS). The sample contains information on 2259 patent applications filed at the Australian patent office (IP Australia) between 1986 and 2005. Only a handful of studies have estimated the R&D depreciation rate and all of them

¹ R&D assets account for a large proportion of intangible assets. Corrado et al. (2009:676) report that they account for approximately 50 per cent of intangible assets in the United States.

rely on indirect inference and strong identifying assumptions. By contrast, the approach proposed in this paper relies on direct observation of inventors' estimates of the revenue streams generated by inventions and is thus genuinely different from existing approaches.² This paper also presents estimates of the effect of patent protection on the depreciation rate. To the best of our knowledge, existing estimates do not differentiate between patented and unpatented inventions. Yet, since the very purpose of patent protection is to slow down the erosion of profit, the depreciation rate of unpatented inventions should be much higher than that of patented inventions. Because not all the patent applications in the AIS were granted, the dataset allows us to study how patent protection affects the depreciation rate. Understanding the magnitude of the difference in the depreciation rate between patented and unpatented inventions may help resolve observed discrepancies in previous estimates and will provide novel insights into the economic effects of the patent system.

To anticipate the results, we find that the depreciation rate is in the lower range of existing estimates and varies between 1 and 5 per cent depending on model specifications. However, we also find that as much as 40 per cent of the decline in value occurs within the first two years. Industry-specific depreciation rates exhibit little heterogeneity. The depreciation rate is lower than the average by 1 percentage point in the basic metals and fabricated metal products industry, and the decline in value that occurs in the early life of an invention is smaller than the average in the pharmaceuticals and medicinal chemicals industry, and larger than the average in the radio, television and communication equipment industry. We further find that patent protection mitigates the depreciation rate. Inventions protected with a patent enjoy a reduction in their depreciation rate by about 1–2 percentage points, thereby providing evidence that patent protection increases the returns to R&D.

The rest of the paper is organised as follows. The next section provides background information on R&D depreciation. Section 3 presents the econometric framework and the data, and section 4 presents the results. Finally, section 5 discusses the implications of the findings and concludes.

² Because patent law requires 'unity of invention', meaning that a patent shall relate to one invention or one inventive concept only, we use the terms 'invention' and 'patent application' interchangeably.

2. R&D depreciation rate and the patent system

This section first discusses the concept of R&D depreciation. It then presents the main approaches that have been proposed in the literature for estimating the R&D depreciation rate (a longer literature review is presented in Mead 2007). The overview serves to emphasise the originality of the method proposed in this paper, as well as report available estimates of R&D depreciation rates for comparison purposes. It also serves to illustrate our point that existing empirical studies do not account for the effect of patent protection on the R&D depreciation rate. Finally, this section discusses the effect of patenting on R&D depreciation.

2.1. Defining R&D depreciation

The concept of R&D depreciation is multifaceted. The knowledge created by R&D investments has both a commercial value and a technological value. It can be embodied in products and processes to deliver an economic benefit, and it can also create opportunities for follow-on innovations. Both commercial and technological value decline over time, suggesting the existence of two distinct depreciation rates. We refer to the decline of appropriable revenues simply as the *depreciation rate of R&D* (our focus in this paper), and the decline in the usefulness of the invention in creating new knowledge as the *obsolescence rate of R&D*. These two objects somehow echo the concepts of exchange value and use value in classical economic theory. The textbook example of this is the wheel. While the wheel has revolutionised transportation systems, has led to innumerable follow-on innovations and is still widely used today (high use value), no one can extract a profit from the use of the invention (no exchange value).

A further definitional refinement relates to the type of the R&D considered: R&D input versus R&D output. These two quantities differ because not all R&D input will be converted into an economically valuable output. A research project may fail to deliver a concrete inventive output or may lead to an inventive output that has no economic value. This distinction matters because it directly affects the nature of the phenomenon being studied. While studies that look at R&D investments (input) inform about the overall *returns to R&D*, studies that focus on inventions (output) informs more specifically about the *returns to technological innovation* (i.e. successful R&D). If anything, the depreciation rate obtained using R&D input measures should be higher than the rate obtained using invention-level data

because of the fact that some R&D projects may fail. The methodology presented in this paper falls within the latter category as it relates to inventive output that was advanced enough to warrant a patent application. This distinction is a key dividing line in the empirical literature.

2.2. Available estimates

A handful of studies have sought to estimate the depreciation rate of R&D. A first formal attempt is that of Pakes and Schankerman (1984), who use patent data (output).³ The authors exploit the fact that the owner of a patent must pay yearly renewal fees in order to maintain a patent in force. They develop a model of the patent renewal decision in which revenues from a patented invention decline deterministically and a patent is renewed for an additional year if the annual revenue at least covers the cost of the renewal fee. They then impose distributional assumptions on invention value and calibrate their model using aggregate data to infer the decay rate of appropriable revenues. This methodology has been refined in a number of ways, in particular by using individual patent data and by accounting for the stochastic nature of the flow of revenues using real option models (Pakes 1986; Lanjouw 1998; Baudry and Dumont 2006; Deng 2007; Bessen 2008).⁴

Other attempts, which rely on R&D expenditures (input) rather than patent data, have also been proposed. Studies in this group are of two main types. A first approach, predominant in the field of accounting studies, relies on firms' financial performance measures. Hirschey and Weygandt (1985) show that R&D expenditures have a positive effect on the market value of firms controlling for the replacement cost of tangible assets. Although the focus of their paper is on the need to capitalise R&D expenditures for accurate accounting, they are able to interpret their model parameters in terms of depreciation rates (or 'amortisation rate' in accounting jargon), but at the cost of identifying assumptions. In particular, they need to assume that R&D investments grow at the equilibrium rate, which is a strong assumption for firm-level studies. Related works include Hall (2005), who also uses

³ Although we use the term 'depreciation rate of R&D' when patent data is used, we are aware that there is not a one-to-one relationship between R&D output and patents. First, not all inventions are patented let alone patentable. Second, not all patents originate from R&D activities.

⁴ Another approach that uses patent data involves modelling the evolution of the number of citations received by patents over time. As a piece of knowledge gradually becomes less useful in generating new knowledge, the number of citations received by a patent should decline (Jaffe and Trajtenberg 1996). It is however unclear that citation data inform about the decay of appropriable revenues. It more likely captures the technological obsolescence of inventions.

firm market value, and Lev and Sougiannis (1996) and Ballester et al. (2003), who use firm earnings.

A second approach that relies on R&D expenditure estimates production models of the economy. Nadiri and Prucha (1996) specify a model of factor demand for the United States manufacturing sector with static price expectations and non-capital input decisions. The depreciation rate of R&D capital is one of the parameters of their model. Other production models include Bernstein and Mamuneas (2006) and Huang and Diewert (2011). Models in this second group are estimated from industry-level data and are therefore not directly comparable with firm-level estimates. The depreciation rate obtained reflects the contribution of R&D investments to the productivity of both the firm conducting the research, and all the other firms in the same industry. Table 1 summarizes the main estimates of R&D depreciation rates. The estimates vary greatly, ranging from almost no depreciation to almost 50 per cent.

Table 1. Overview of R&D depreciation rate

Article	Key data	Model	Unit	Rate
Pakes and Schankerman (1984)	Granted patents	Patent renewal	Invention	0.25
Pakes (1986)	Granted patents	Patent renewal	Invention	0.11–0.19
Lanjouw (1998)	Granted patents	Patent renewal	Invention	0.02–0.06
Deng (2007)	Granted patents	Patent renewal	Invention	0.06–0.11
Bessen (2008)	Granted patents	Patent renewal	Invention	0.13–0.27
Hirschey and Weygandt (1985)	R&D expenditures	Accounting	Firm	0.02–0.17
Lev and Sougiannis (1996)	R&D expenditures	Accounting	Firm	0.11–0.20
Ballester et al. (2003)	R&D expenditures	Accounting	Firm	0.02–0.46
Hall (2005)	R&D expenditures	Accounting/ Production function	Firm	-0.06–0.28
Nadiri and Prucha (1996)	R&D expenditures	Production function	Industry	0.12
Bernstein and Mamuneas (2006)	R&D expenditures	Production function	Industry	0.18–0.29
Huang and Diewert (2011)	R&D expenditures	Production function	Industry	0.01–0.29

Notes: Point estimates of depreciation rates reported. The depreciation rates in Lev and Sougiannis (1996) are computed as the average values of the parameters δ_k in Table 3.

Although existing studies differ widely in their scope and methodology, one common trait is that they rely on indirect inference to estimate the depreciation rate.⁵ By contrast, the

⁵ One exception is surveys on the ‘service life’ of R&D projects. This approach has been adopted by some statistical offices in their efforts to capitalise R&D expenditures in national account systems (Peleg, 2008; Ker, 2013). One strength of this approach is that it produces service lives for the different components of R&D (basic research, applied research, and development). Weaknesses include the fact that it relies on a stated service life (as opposed to a revealed service life), and that service life is expressed in years and is, therefore, not directly comparable with the literature on R&D depreciation.

methodology adopted in this paper relies on direct inference. Our data on inventor estimates of invention revenue streams allow us to infer the depreciation rate in a way that is free of identifying assumptions.⁶ In addition, no previous research has explicitly studied the effect of patent protection. While estimates that rely on granted patents are only informative about the decay rate of revenues from patented inventions, estimates that rely on R&D expenditures mix both patented and unpatented inventions (as well as successful and unsuccessful R&D projects). Estimating the effect of patent protection on the depreciation rate is thus a step forward in bringing these two sets of estimates closer to each other.

2.3. Effect of patent protection on the depreciation rate

As Griliches (1979:101) observes, the depreciation rate of revenues accruing to the innovator derives from two related points regarding the market valuation of the invention: the loss in specificity of the knowledge as it leaks to other firms in the industry ('imitation effect'); and the development of better products and processes which displace the original innovation ('displacement effect'). This observation immediately suggests two ways in which patent protection may reduce the depreciation rate. First, patent protection reduces the imitation effect as it confers the right to exclude others from making, using, selling and importing the invention. Second, patent protection also slows down or blocks follow-on research by competitors (Scotchmer 1991; Bessen and Maskin 2009), thereby mitigating the displacement effect.

The literature is equivocal about both of these effects. On the one hand, patent protection is an imperfect appropriability mechanism. Patent rights are costly to enforce and do not prevent competitors from inventing around the technology. First, while it is well recognised that many firms apply for patents to protect against imitation (Cohen et al. 2000; Blind et al. 2006; de Rassenfosse 2012), the actual effectiveness of patent protection has been questioned. Enforcing a patent requires considerable resources, either financial resources to defend the validity of a patent in court or other resources such as a large patent portfolio to increase negotiation power and settle before trial (Hall and Ziedonis 2001; Farrell and Merges 2004; Weatherall and Webster forthcoming). Second, patent protection is ineffective against imitators inventing around an innovation (Mansfield et al., 1981; Gallini 1992). To

⁶ Of course there are also limitations associated with our approach, in particular regarding the fact that we use the inventor's estimate of the revenue stream. We discuss the caveats in sections 3 and 4. Note that, in contrast to service lives estimates, our approach relies on a revealed-approach for estimating the depreciation rate (a stated-approach would involve asking respondents directly about the depreciation rate).

protect themselves against substitute technologies, firms sometimes resort to a ‘patent fencing’ strategy which involves filing multiple patents per innovation (Reitzig, 2004). On the other hand, scholars have shown that patent protection increases the value of inventions (Arora et al. 2008; Jensen et al. 2011) or the value of the patenting firm (Ceccagnoli 2009), thereby providing evidence that patenting strengthens firms’ appropriability conditions despite imperfections. As these concerns have the potential to undermine the benefit of patent protection, the empirical analysis shall touch upon these issues.

There is, however, one important proviso to our approach to bear in mind. Patent protection is a costly and substitutable good and firms self-select into the patent system. The cost is both monetary (actual cost of patenting) and non-monetary (disclosure requirement in patent law) and authors have shown that it affects the patenting decision (Horstmann et al. 1985; Zaby 2010; de Rassenfosse and van Pottelsberghe, 2013). The substitutability of patent protection arises from the alternative appropriation mechanisms such as lead time and the availability of complementary assets (Teece 1986; Cohen et al. 2000; Arora and Ceccagnoli 2006). Therefore, under some conditions it might well be that inventions kept secret enjoy a lower depreciation rate than inventions submitted to the patent office. The Coca-Cola formula is the archetypal example of an innovation that would have depreciated at a much faster pace if it were patented. In this paper the effect of patent grant is estimated for firms that self-select into the patent system, i.e. no secrecy in the sample. Observations in the AIS are patent applications, some of which are granted, some of which are not.

3. Framework and data

3.1 Empirical framework

There is no unique pattern in the evolution over time of the revenue streams of inventions. While some inventions may produce most revenue in their early life, others may deliver no return until late. We call $V(t)$ the amount of appropriable revenues remaining at time t (that is, from $t \rightarrow \infty$). Invention value is subject to high uncertainty and is consequently very difficult to predict.⁷ However, it is necessarily the case that, ex post, $V(t)$ is a declining function of time. We follow previous convention and model invention value at time t using an exponential decay function:

⁷ We discuss this issue in section 4.3.

$$V(t) = V(0)e^{-\delta t} \quad (1)$$

where δ is the depreciation parameter. The model assumes a constant depreciation rate over time, and we show in section 4.2 that our data supports that assumption. Dividing equation (1) by $V(0)$ and taking to the log, the empirical counterpart of equation (1) can be written as:

$$\ln \frac{V_{it}}{V_{i0}} = -\delta t + \varepsilon_{it} \quad (2)$$

where i denotes an invention and δ is the parameter to be estimated.⁸ Note that, in its initial form, equation (2) does not include a constant term – an intercept c different from 0 would imply that $E[\ln(V_{i0}/V_{i0})] = c$, which cannot be true. However, given that the youngest inventions in the sample are two years old, a constant term different from 0 can be interpreted as the decline in value that occurs within the first two years.

We do not observe the full sequence of invention values $\{V_{it}\} \forall i, t$. We observe invention value at time 0 and the residual invention value at the time of the survey. Heterogeneity comes from that fact that inventions belong to cohorts of different vintages. Thus, we observe $\{V_{it}: t = 0, t_i; t_i \neq 0\}$.⁹ Grouping observations by cohort and letting a denote a cohort of age t , that is $t_i = a$, equation (2) can be written as (including a constant term):

$$\ln \frac{V_{ia}}{V_{i0}} = c - \delta a + \varepsilon_{ia} \quad (3)$$

where the error-term $\varepsilon_{ia} \sim N(0, \sigma_a^2)$ in the baseline specification. We model variations in the depreciation rate δ as a linear function of covariates:

$$\ln \frac{V_{ia}}{V_{i0}} = c - (\mathbf{x}'_i \boldsymbol{\beta}) a + \varepsilon_{ia} \quad (4)$$

⁸ We explain in section 4.2 that the regression equation (2) also encompasses the class of declining balance models and is, therefore, quite general.

⁹ It implies that the depreciation rate of appropriable revenues will be estimated from a mix of: within variations in invention value and between variations in value.

where $x_i'\beta$ is the inner product between the vector of covariates x_i and the vector of parameters β . It is clear from equation (4) that all the explanatory variables must be interacted with the age variable. Equation (4) will be estimated with OLS as well as with alternative regression models. We will use a generalised linear model to account for the fact that the dependent variable is not normally distributed as well as robust regression models to account for a difference in the trustworthiness of estimates across vintages.

3.2 Data sources

The empirical analysis combines data from four sources. The main data source is the AIS and it is complemented with information from patent databases.

3.2.1 Australian Inventor Survey (AIS)

In 2007 the Melbourne Institute at the University of Melbourne has conducted a survey of patent applications by Australian inventors submitted to the Australian Patent Office from 1986 to 2005. Each surveyed inventor was asked questions related to the characteristics of the invention, including questions about invention value. There are 3862 inventions in the database and information on value is available for 2558 of them. A complete description of the survey methodology is provided in Webster and Jensen (2011). Non-response biases for the dependent variable are investigated in section 4.1.

3.2.2 IP Australia's AusPat database

The AusPat database from IP Australia is used to get information on the priority date of the patent application as well as their grant status. The priority date is the date of the first filing of an application for a patent. It is used to compute the age of the invention. An alternative approach involves computing the age from the date of filing at IP Australia, but this would miss the life of the invention prior to entering the patent system in Australia. Approximately two-thirds of inventions with non-missing invention value were eventually granted patent protection. Two patent applications were still pending at the time of the study.

3.2.3 Patstat

The European Patent Office worldwide patent statistical database Patstat is used to get information on the family size and the IPC codes of each patent application. The family size is defined as the number of jurisdictions in which patent protection was sought. We adopt the extended INPADOC family definition, which groups together applications that are directly or

indirectly linked through priorities (see Martinez 2010 for more information on patent families). International Patent Classification (IPC) codes represent the different areas of technology to which the patents pertain. They are assigned by examiners at the patent office and are thus homogeneous across patents.

3.2.4 IPC-ISIC Concordance Table

Patents have been assigned to the appropriate industries using the empirical concordance table between IPC and International Standard Industrial Classification (ISIC) codes provided by Schmoch et al. (2003). The concordance table was built by investigating the patenting activity in technology-based fields (IPC) of more than 3000 firms classified by industrial sector (ISIC). When a patent contains more than one IPC code, the industry allocation is performed on a fractional basis.

3.3 Dependent variable

The dependent variable is the log of the proportion of invention value remaining at the time of the survey ($\ln V_{ia}/V_{i0}$). It is constructed from the following three survey items:

- *G1. To date, what is your estimate of sales revenue from products and processes using this invention?* [0 < \$100,000; \$100,000 to \$500,000; \$500,000 to \$1m; \$1m to \$2m; \$2m to \$10m; > \$10m; unsure];
- *G2. If you were selling this patent or invention today, what price would you be willing to accept for it?* [0 < \$100,000; \$100,000 to \$500,000; \$500,000 to \$1m; \$1m to \$2m; \$2m to \$10m; > \$10m; unsure]; and
- *G3. If this patent has been licensed, what is your best estimate of the licensing revenues to date?* [0 < \$100,000; \$100,000 to \$500,000; \$500,000 to \$1m; \$1m to \$2m; \$2m to \$10m; > \$10m; unsure].

The variable V_{ia} is the residual value for patents of age a and corresponds to question G2. The variable V_{i0} is the total value at $t = 0$. It can be computed as $(G1 + G3) + G2$. Since the data is ordinal, the dependent variable was constructed from the mid-point value of each category (the last category was arbitrarily assigned a value of \$15m), although we note that alternative methodologies for converting categories into actual dollars will be tested.

Contrary to the existing approaches outlined in section 2, which rely on indirect inference to determine appropriable revenues, the dependent variable used in this paper is a direct measure of revenues. Although there may be a bias in inventors' evaluation of the value of their inventions, such bias is mitigated by the use of ordinal variables (at the cost of precision, however). Another potential source of bias relates to the fact that inventions belong to cohorts of different vintages. The remaining value (question G2) is subject to a greater deal of uncertainty for younger cohorts, and respondents may experience greater difficulty in recollecting revenues earned for older inventions (questions G1 and G3). This issue will be dealt with in the empirical analysis.

3.4 Covariates

Age of the patent (a). Computed as the number of years elapsed between the year of the priority patent application and the year of the survey (2007).

Grant status of the patent (grant). Dummy variable takes the value 1 if the invention was granted patent protection and 0 otherwise. Australia's patent law decrees that a patent right should be granted only for inventions that have a high degree of inventive merit over existing knowledge. The decision to grant a patent is done after a thorough examination of international prior art conducted by specialist patent examiners within IP Australia. It is therefore an exogenous event based on technological merit, not commercial value.

International protection (intl protection). Dummy variable takes the value 1 if the invention is protected in at least one other country, that is if the INPADOC family covers at least two jurisdictions. Seeking international expansion for a patent is a complex and expensive process that requires a certain level of commitment from its owner. We use this variable to capture the ability of the owner to defend the patent in court in case of infringement.

Other patents involved (other patents). The AIS contains information on the number of patents that were also used to develop the product. It is an ordinal variable with five categories [none; 1 to 5; 6 to 10; 11 to 20; 20+]. For the purpose of the analysis, the variable 'other patents' is a dummy variable that takes the value 1 if at least one other patent is used to develop the product. Without using the terms 'patent fences' and 'patent thickets', the presence of other patents suggest that it becomes more difficult for competitors to invent around a technology. Similarly, patent protection may matter less for technologies that involve several patented components. Even if patent protection is not obtained for one

component, another component may enjoy patent protection thereby providing effective protection for the whole technology.

Private companies (private). Dummy variable takes the value 1 if the invention belongs to a private company and 0 if it belongs to a public research organisation or an individual inventor.

Industry dummies. Dummies corresponding to the main ISIC code of the patent.

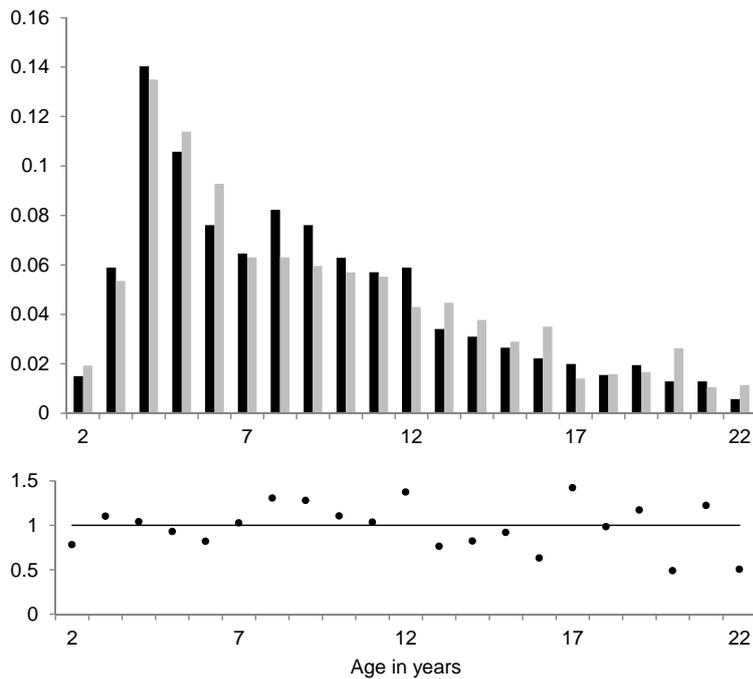
4. Results

4.1 Descriptive statistics

There were 3862 inventions surveyed in the AIS and information on value is available for 2558 of them. Among these, 2259 inventions (88 per cent) are matched to the Patstat database.¹⁰ We did not find evidence of bias in the reporting of invention value. Such a bias can be investigated along two dimensions that are available from an external source (Patstat and AusPat databases): the number of jurisdictions in which patent protection is sought (the family size) and the age of inventions. The average family size is 3.34 for inventions for which information on value is provided ($N=2259$), 3.23 for inventions with no information on value ($N=1141$), and the difference is not statistically significant (p-value of 0.38). Similarly, the average age is 8.82 years for inventions with information on value and 9.06 years for inventions lacking information on value, and the difference is not statistically significant (p-value of 0.18). The age profile of inventions is presented in the upper panel of Figure 1 for the series of inventions with information on value (black bars) and missing information on value (grey bars). The ratio of frequencies between the two series, depicted in the lower panel, oscillates around 1 and does not suggest the presence of bias.

¹⁰ In theory, all the observations should be matched to the Patstat database. There are, however, coverage problems in the Patstat database for patents filed at IP Australia. See de Rassenfosse et al. (2013) for a discussion. We investigate the effect of a potential selection bias in section 4.3.

Figure 1. Histogram of invention ages and ratio of missing to non-missing value information



Notes: Upper panel: histograms of invention ages by availability of value information (black: available, grey: missing). Lower panel: ratio of frequencies between the two series.

Table 2 presents descriptive statistics of the sample used. Since the dependent variable is the logarithm of the ratio of values, it is always negative. The mean of the dependent variable is -0.96 and the median is -0.69 (not reported). The skewness of the dependent variable is explained by the predominance of more recent inventions in the sample. Inventions in the sample are older than two years and the average age is 8.82 years. There are 47 per cent of observations from private entities, and the overall grant rate is 67 per cent. About 52 per cent of inventions are part of an international patent family, and 35 per cent of inventions come with at least one other patent application.

Table 2. Descriptive statistics

	Min	Mean	Max	Std. Dev
$\ln V_{ij}/V_{i0}$	-6.40	-0.96	-0.0033	0.99
<i>a</i>	2	8.82	24	4.69
<i>grant</i>	0	0.67	1	-
<i>private</i>	0	0.47	1	-
<i>intl protection</i>	0	0.52	1	-
<i>other patents</i>	0	0.35	1	-

Notes: N = 2259.

4.2 Estimates of depreciation rates

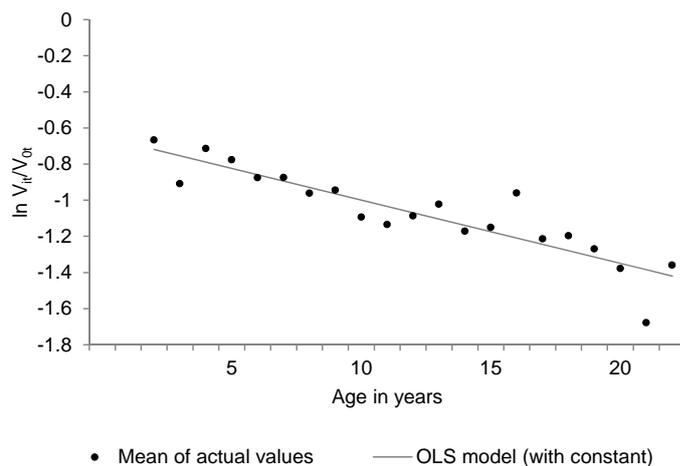
Table 3 presents baseline estimates of equation (4). Results using an OLS regression model without a constant in column (1) suggest that appropriable revenues decrease at a rate of 10 per cent annually. However, this model violates the basic OLS assumption that the mean of residuals be equal to zero, which typically calls for the inclusion of a constant term. Allowing for a constant term c in column (2) reduces the depreciation parameter to 3.7 per cent. The estimated value for the earliest observations available is $E[\ln(V_{i2}/V_{i0})] = c + \delta * 2$, and the constant term c can therefore be interpreted as the decline in value that is not accounted for by the depreciation parameter. In other words, the OLS regression model suggests that 47 per cent ($= 1 - e^c$) of the decline in value occurs within the first two years. Figure 2 depicts the model fit. It suggests that the linearity assumption of the depreciation rate holds.¹¹ A close look at the residuals suggests the presence of heteroscedasticity (the variance of residuals increases with age, not reported). Although standard errors are clustered by cohort, a more appropriate distributional assumption or a more appropriate treatment of likely outliers could improve estimation. We investigate these two issues in turn.

¹¹ More flexible specifications of the decay function (up to the third-order polynomial of age) were considered but did not perform better in terms of the Akaike and Bayesian information criteria than the linear model.

Table 3. Depreciation parameter with various estimation methods

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Method:</i>	OLS	OLS	GLM	Robust	Quantile	Robust	Quantile
a	-0.093*** [16.66]	-0.037*** [7.34]	-0.034*** [6.96]	-0.031*** [9.56]	-0.023*** [7.47]	-0.015*** [3.21]	-0.014*** [2.66]
$a \times private$						-0.021*** [6.64]	-0.017*** [4.79]
$a \times industry\ dummies$						Y***	Y***
Constant		-0.639*** [11.39]	1.370*** [19.06]	-0.488*** [15.00]	-0.534*** [17.48]	-0.477*** [14.75]	-0.497*** [13.77]
Observations	2259	2259	2259	2259	2259	2259	2259
R ²	0.031	0.031	0.029	0.031	0.031	0.057	0.056

Notes: Standard errors clustered by cohort in columns (1), (2), and (3). t statistics reported in brackets. R^2 is the square of the correlation coefficient between the predicted values of the dependent variables and their actual values. ***, ** and * denote significance at the 1%, 5%, and 10% probability threshold, respectively.

Figure 2. Actual and predicted values, by age

Notes: Series for the OLS model is obtained from column (2) of Table 3.

The OLS regression model requires the dependent variable to be normally distributed. The dependent variable actually takes its value on the interval $[0, -\infty)$ such that the normality assumption is violated. In column (3), we assume that the dependent variable conditional on the covariates follows a Gamma distribution and we estimate a generalized linear model (GLM).¹² The estimated coefficient is -0.034 and corresponds to a marginal effect at mean of 0.033. The marginal effect is very close to the OLS estimate and the residuals still exhibit

¹² The dependent variable is transformed to $-\ln(V_{it}/V_{i0})$ so that it takes its value on the interval $[0, +\infty)$.

heteroscedasticity, suggesting that GLM regression does not improve the result. Heteroscedasticity is probably a consequence of the fact that inventions belong to cohorts of different vintages, such that the level of trustworthiness of estimates varies. Results of a robust regression model that down-weights potential outliers is reported in column (4). The depreciation parameter remains in a similar range, although the constant term is closer to zero as compared with column (2). The estimated weights decrease with age, meaning that older observations are given less importance in the regression analysis.¹³ A quantile regression model is presented in column (5). The quantile regression model estimates the effects of covariates on the median of the dependent variable rather than on its mean and is another way of accounting for potential outliers (Koenker and Bassett 1978). The estimated depreciation rate is slightly lower (2.3 per cent) and the constant term is equal to -0.53. The constant term suggests that approximately 40 per cent of the decline in value occurs within the first two years.

Although the framework adopted is that of an exponential decay model, the parameter can also be interpreted in terms of a declining balance model. Such a model takes the form $V_{ia} = V_{i0}(1 - \delta)^a$ and can be written as $\ln V_{ia}/V_{i0} = \ln(1 - \delta) a = \beta a$. Thus, the declining balance depreciation rate can easily be recovered from the estimated parameter β . It corresponds to $\delta = 1 - e^\beta$. Note that for β small, $\delta \cong \beta$ such that both models give sensibly similar results.

Regressions presented in the last two columns allow for a differentiated effect for private companies. Inventions by private companies depreciate by about two percentage points more than inventions by public research organisations and individuals, probably owing to greater competitive pressure. The regressions also include dummies for seven industries that have at least 100 observations each. These seven industries account for more than 80 per cent of inventions and the corresponding dummies are jointly significant. Industry-specific estimates of the R&D depreciation rate are presented in Table 6 in Appendix A for the selected industries. Point estimates vary between 1 and 5 per cent but most of the variations are not statistically significant. The depreciation rate is significantly lower than the reference group (patents in all bar the seven industries considered) for both the quantile and the robust regression models in the basic metals and fabricated metal products industry. The decline in value that occurs in the early life of an invention is smaller than the reference group in the

¹³ The average weight is 0.90 at age < 5 and 0.85 at age > 15. The correlation coefficient between age and the weight variable is -0.08 and is significant at the 1 per cent probability threshold.

pharmaceuticals and medicinal chemicals industry (the constant term -0.062 for the quantile regression model in column (4) is equivalent to a drop of value in the first two years of 6 per cent) and larger than the reference group in the radio, television and communication equipment industry (with almost 50 per cent of the value disappearing within the first two years).

The next sets of results presented in Table 4 estimate the effect of patent protection on the depreciation rate using both the robust regression and the quantile regression models. The grant effect, associated with the variable ' $a \times grant$ ', is straightforward to interpret. It corresponds to the percentage points reduction in the depreciation rate. For instance, the value of 0.01 in column (1) suggests that inventions that enjoy patent protection have a depreciation rate that is on average 1 per cent lower than that of unpatented inventions. The corresponding rate for the quantile regression model in column (4) is 1.6 per cent.¹⁴ One must be careful when interpreting the grant effect because of the limited information available. Ideally one would observe the full sequence of values together with the grant and lapse events to estimate the effect of one additional year of protection on the depreciation rate. Unfortunately, however, the sequence of value in the AIS is incomplete such that the correct interpretation of the grant effect is the yearly reduction in the depreciation rate over the life of inventions, given an average length of protection of eleven years (which is the average length of protection at IP Australia as indicated in Sutton 2009).

Mitigating factors for the grant effect are investigated in columns (2)–(3) and (5)–(6). In particular, the ability to defend the patent in court may matter more than the actual grant and may drive most of the effect. We use the variable 'intl protection' as a proxy variable and we break down the grant effect into two groups: patent holders that have applied for international patent protection (they may have deeper pockets and/or be more willing to enforce their patent rights), and patent holders that have not. The corresponding parameters in columns (2) and (5) are not significantly different from each other. A second concern that may affect the estimated parameter is that patent protection may matter less for technologies that involve several patented components. Even if patent protection is not obtained for one component, another component may enjoy patent protection thereby providing effective protection for the whole technology. This issue is investigated in columns (3) and (6) with the variable 'other patents'. While the presence of other patents seems to further slow the erosion

¹⁴ The OLS estimate of the grant effect is 0.009 and is significant at the 10 per cent probability threshold.

of profits (by about 1 percentage point), the effect of patent protection remains positive and significant in both regression models.

Table 4. Effect of patent grant on depreciation rate

	(1)	(2)	(3)	(4)	(5)	(6)
	Robust regression			Quantile regression		
<i>a</i>	-0.024***	-0.024***	-0.025***	-0.031***	-0.031***	-0.034***
	[4.04]	[4.02]	[4.30]	[4.02]	[4.03]	[4.30]
<i>a</i> × <i>grant</i>	0.010**		0.009**	0.016***		0.017***
	[2.57]		[2.30]	[3.09]		[3.18]
<i>a</i> × <i>grant</i> × (<i>intl protection</i> = 1)		0.010**			0.018***	
		[2.47]			[3.19]	
<i>a</i> × <i>grant</i> × (<i>intl protection</i> = 0)		0.010**			0.014**	
		[2.19]			[2.50]	
<i>a</i> × <i>other patents</i>			0.009***			0.011**
			[2.72]			[2.46]
<i>a</i> × <i>private</i>	-0.022***	-0.022***	-0.023***	-0.019***	-0.020***	-0.019***
	[7.05]	[7.03]	[7.30]	[4.58]	[4.83]	[4.39]
<i>a</i> × <i>industry dummies</i>	Y***	Y***	Y***	Y***	Y***	Y***
Constant	-0.454***	-0.455***	-0.458***	-0.423***	-0.429***	-0.417***
	[13.66]	[13.62]	[13.72]	[9.72]	[9.87]	[9.28]
Observations	2259	2259	2259	2259	2259	2259
R ²	0.058	0.058	0.059	0.054	0.055	0.054

Notes: t statistics reported in brackets. R² is the square of the correlation coefficient between the predicted values of the dependent variables and their actual values. ***, ** and * denote significance at the 1%, 5%, and 10% probability threshold, respectively.

4.3 Sensitivity analysis

Table 5 presents a series of robustness tests aimed at assessing the validity of the results. A first concern relates to the fact that observations in the sample belong to cohorts of different vintages. While future revenues are more uncertain for younger cohorts (question G2), past revenues may be more difficult to estimate accurately for older cohorts (questions G1 and G3), leading to a dependent variable that may be inconsistently measured across cohorts. Figure 3 and Figure 4 in Appendix B depicts the variable V_0 (=G1+G2+G3) by cohort. There is no noticeable difference in the mean of invention value across cohorts (except at age 24, Figure 3), and the variable varies widely within cohorts as shown by the box plot in Figure 4. However, a linear regression of V_0 against the age variable suggests that the reported value

declines slightly with age (not reported). This effect could be due either to an underestimation of the past revenues (which would affect older inventions) or an overestimation of the future revenues (which would affect younger inventions). The sample used in column (1) is restricted to inventions in a narrower age range. It includes inventions that are between five and 12 years old. This selection criterion filters out (approximately) the 20 per cent youngest inventions and the 20 per cent oldest inventions. Results presented in the upper panel of Table 5 must be compared with those in column (1) of Table 4, while results in the lower panel must be compared with those in column (4) of Table 4. The figures remain in a similar range. The estimated depreciation rate is about 1 percentage point higher while the grant effect is half a percentage point stronger.

Second, we were careful to explain in the previous section that the correct interpretation of the grant effect is ‘the yearly reduction in depreciation rate over the life of inventions, given an average length of protection of eleven years’. We are left with this interpretation because the structure of the data does not allow us to associate the grant and lapse events to revenue stream estimates. However, it is possible to obtain a more precise picture of the grant effect by focusing on the youngest inventions, which are more likely to enjoy patent protection. The results in column (2) are estimated on the sample of inventions with a maximum age of eight years, capturing roughly half of the inventions. Doing this leads to an estimate of the grant effect that is three times as large as that reported in Table 4. Inventions protected with a patent enjoy a reduction of the depreciation rate of about 3–5 percentage points (compared with a depreciation rate that is estimated at 4–7 per cent). Consistent with this finding, the grant effect becomes negligible when the regressions are estimated on the sample of inventions older than eight years (not reported). In other words, while the overall effect of patent protection over the life of the invention is 1–2 percentage points, the effect of active patent protection (i.e., over the patent life) is possibly three times as large.

A third concern relates to the fact that some inventions in the sample were transferred or sold to a third-party, casting doubt on the accuracy of the revenue stream estimates. Regression results presented in column (3) of Table 5 are performed on a sample that excludes 539 such inventions.¹⁵ The results remain largely unchanged.

¹⁵ We exclude inventions for which the following questions were answered positively: ‘Has there been any attempt to license or sell this patent to a third party?’ and ‘Has there been any attempt to transfer this patent to a

Fourth, we were not able to match twelve per cent of the observations to the Patstat database (see section 4.1). Including these observations in the regression leaves the results unchanged, as shown in column (4).

A final concern relates to the fact that we have arbitrarily taken the mid-point value of each category of the ordinal variables to construct the dependent variable. In columns (5) and (6) we test whether the results are robust to alternative imputation methods. In column (5) we assume that observations are uniformly distributed in the range covered by their category (0 to \$100,000, \$100,000 to \$500,000, etc.), while in column (6) we assume that observations are distributed according to a Beta distribution that is skewed to the left. Again, the results are roughly similar.

Table 5. Robustness tests

	(1)	(2)	(3)	(4)	(5)	(6)
	Y5–Y12	≤ Y8	No transfer	All obs.	Uniform	Beta
Robust regression						
<i>a</i>	-0.036***	-0.039***	-0.022***	-0.027***	-0.026***	-0.026***
	[3.41]	[2.66]	[3.21]	[5.16]	[3.84]	[3.74]
<i>a</i> × <i>grant</i>	0.014***	0.030***	0.010**	0.008**	0.010**	0.012**
	[2.71]	[4.10]	[2.30]	[2.13]	[2.21]	[2.53]
Constant	-0.316***	-0.391***	-0.482***	-0.465***	-0.458***	-0.399***
	[4.35]	[6.26]	[12.52]	[14.59]	[11.92]	[10.20]
Quantile regression						
<i>a</i>	-0.042***	-0.069***	-0.025***	-0.032***	-0.036***	-0.042***
	[3.82]	[2.98]	[2.92]	[5.66]	[3.61]	[4.19]
<i>a</i> × <i>grant</i>	0.023***	0.051***	0.012**	0.013***	0.018***	0.019***
	[4.27]	[4.30]	[2.20]	[3.29]	[2.70]	[2.91]
Constant	-0.270***	-0.220**	-0.472***	-0.449***	-0.286***	-0.164***
	[3.58]	[2.21]	[9.49]	[13.26]	[5.12]	[2.89]
Observations	1319	1227	1721	2556	2259	2259

Notes: The regressions control for industry dummies and the ‘private’ dummy. ***, ** and * denote significance at the 1%, 5%, and 10% probability threshold, respectively.

Additional robustness tests were performed but are not reported. First, we checked that the results obtained for the ‘intl protection’ variable are not affected by our choice of a dummy variable rather than the actual family size. We have interacted the ‘grant’ variable

spin-off company?’ Therefore, we are not able to differentiate between inventions that were sold from inventions that were licensed and we also excluded the latter.

with the family size and the results did not change. Second, we made sure that our interpretation of the ‘other patents’ variable, which takes the value of 1 if at least one other patent was used to develop the product, is correct. While we implicitly assume that these other patents belong to the same firm, the possibility exists that they belong to other firms. We have no way of ruling out this possibility with certainty. To hint towards an answer, we exploit that fact that inventors may have responded multiple times to the survey if they were listed in more than one patent. Inventors who reported that one of their patents involves other patents were 2.5 more likely to have filed another patent at IP Australia than inventors who did not mention that other patents were involved. This finding is consistent with our assumption that the other patents belong to the same firm. We have also estimated the regression model on a sample that excludes inventions that involve more than five other patents and inventions that were licensed. The possibility that patents from other firms are involved is indeed more likely when a large number of patents is concerned (as in the case in complex products industries) or when the focal patent was licensed (a sign that cross-licensing may have occurred). Doing this leads to coefficients that remain broadly similar, although the significance of the variable ‘other patents’ has declined (p-values of 0.056 and 0.112 for the robust and the quantile regression models, respectively).

5. Discussion and concluding remarks

This paper produces estimates of the private R&D depreciation rate using survey data on patent applications submitted to IP Australia. Its novelty lies in the fact that it involves a new methodological approach and addresses a new research question. First, to the best of our knowledge, it is the first time that the revenue streams of inventions are observed. This feature of the data allows us to estimate the R&D depreciation rate in a very natural way that is free of identifying assumptions. This is in stark contrast with previous studies which all rely on indirect inference. We find that the yearly depreciation rate is in the lower range of existing estimates and varies between 1 and 5 per cent, depending on model specifications. However, we also find that as much as 40 per cent of the decline in value occurs within the first two years. We find surprisingly little variation across industries. The depreciation rate is lower than the average by 1 percentage point in the basic metals and fabricated metal products industry, while the decline in value that occurs in the early life of an invention is smaller than the average in the pharmaceuticals and medicinal chemicals industry, and larger

than the average in the radio, television and communication equipment industry. Second, another feature of the data is that it relates to patent applications instead of patents granted. Because not all patent applications in the AIS were granted, the data allow us to estimate the extent to which patent protection slows the erosion of profits. As far as we know, this analysis is the first of its kind. The literature on patent renewals has largely considered that the depreciation rate is exogenous to patent protection. That is, the optimal renewal period is chosen given an intrinsic depreciation rate. This paper goes one step further by studying the effect of the patent protection on depreciation rate. However, we observe invention value at two points in time such that we are not able to study the effect of patent protection in detail (that is, as a function of the length of patent protection). Rather, the grant effect reflects an average length of protection of eleven years. We find that patent protection reduces the depreciation rate by 1–2 percentage points over the life of the invention.

A potential limitation of our study relates to the lack of R&D expenditure data. Although the theoretical literature has long established the endogenous nature of R&D investment and R&D depreciation (Caballero and Jaffe 1993; Jovanovic and Nyarko 1998; Pacheco-de-Almeida 2010), existing empirical research has not been able to account for the effect of R&D investment on the depreciation rate. This paper is no exception. Future research showing how R&D depreciation and R&D investment affect each other and how this relationship is mitigated, e.g. by the strength of competition would be particularly welcome.

The results presented in this paper have implications that extend beyond academic interest. First, estimates of R&D depreciation rates are of immediate relevance to statistical offices around the world in their efforts to capitalise R&D investments in their national account systems (OECD 2010). Second, they are also relevant to the growing number of financial institutions that take patents as collateral for loans (Mann 2005; Fischer and de Rassenfosse 2011). Because a large proportion of the decline in value occurs early, lenders are well advised to wait for technological uncertainty to dissipate before taking patents as collateral. Third, existence of a grant effect can be given various economic interpretations. It is evidence that patent protection slows down the process of creative destruction (Caballero and Jaffe 1993); increases the private returns to R&D (Hall 2005); and is associated with a

premium (Arora et al. 2008; Jensen et al. 2011).¹⁶ These different interpretations all relate to the same phenomenon, namely the fact that patent protection assures greater appropriability.

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¹⁶ It is important to emphasize that the present results are conditional on the existence of an inventive output. The overall effect of patent protection is to encourage technological progress and, therefore, to stimulate creative destruction.

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Appendix A. Industry-specific depreciation rates

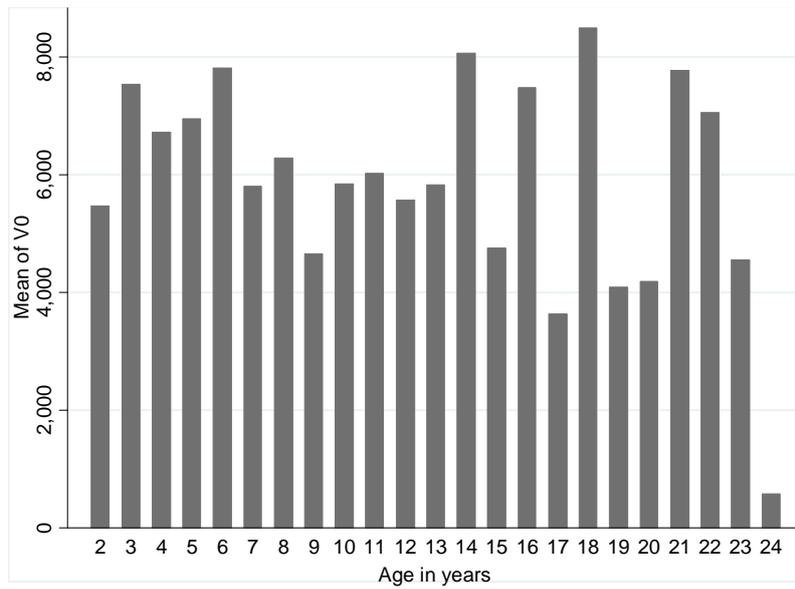
Table 6. Industry-specific depreciation rates

	(1)	(2)	(3)	(4)
	Robust regression		Quantile regression	
<i>Depreciation rate (a)</i>				
Reference group	-0.023	-0.029	-0.018	-0.016
2401	-0.034	-0.030	-0.029*	-0.013
2423	-0.009**	-0.023	-0.011	-0.045***
2728	-0.034*	-0.035	-0.024	-0.029*
2900	-0.037***	-0.035	-0.032***	-0.036***
3200	-0.024	-0.016	-0.021	-0.002**
3400	-0.037*	-0.035	-0.026	-0.011
3600	-0.036**	-0.031	-0.034***	-0.038***
<i>Early drop in value (constant term)</i>				
Reference group	-0.499	-0.436	-0.518	-0.531
2401		-0.545		-0.613
2423		-0.363		-0.062***
2728		-0.470		-0.472
2900		-0.519		-0.478
3200		-0.573		-0.683**
3400		-0.515		-0.639
3600		-0.544		-0.490

Notes: N = 2259. Estimates for the reference group are all significantly different from 0 at the 1 per cent probability threshold. ***, ** and * indicate that the estimate for the specific industry is significantly different from the estimate for the reference group at the 1, 5 and 10 per cent probability 2401: ‘chemicals and chemical products (excl. 2423)’; 2423: ‘pharmaceuticals and medicinal chemicals’; 2728: ‘basic metals and fabricated metal products’; 2900: ‘machinery and equipment n.e.c.’; 3200: ‘radio, television, and communication equipment’; 3400: ‘motor vehicles, trailers and semi-trailers’; 3600: ‘furniture and n.e.c.’. Reference group is all other industries.

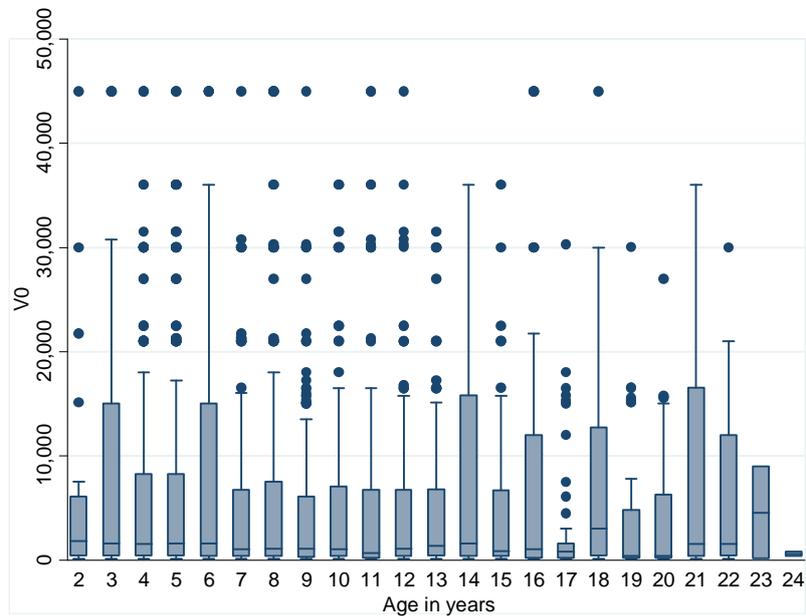
Appendix B. Bias in the reporting of invention value

Figure 3. Mean of initial value (V_0) by cohort



Notes: V_0 in thousands AUD.

Figure 4. Box plot of initial value (V_0) by cohort



Notes: V_0 in thousands AUD.